

Stacking.

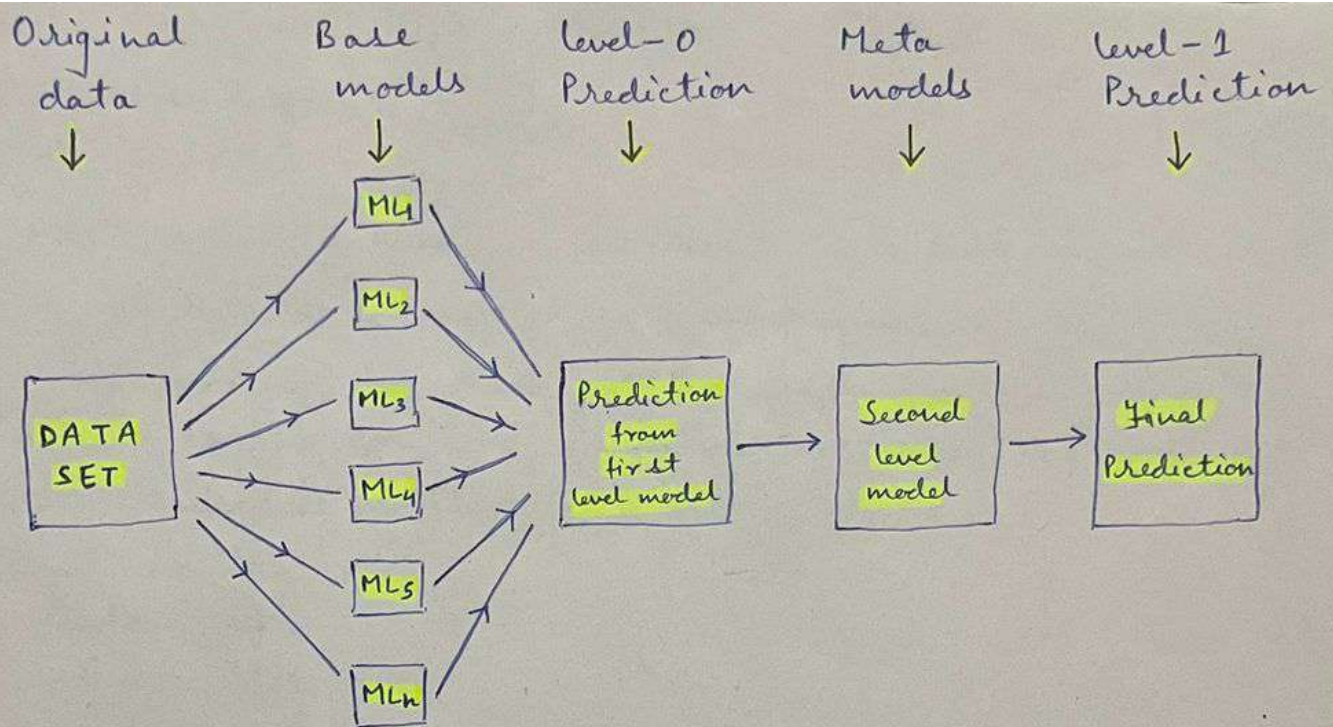
Ensemble technique where numerous weak learners are ensembled in parallel manner in such way that by combining them with meta learners, we can predict better predictions for the future.

Stacking is also known as stacked generalization. All sub-models equally participate as per their performance weights and build new model with better prediction.

Weak learners are ensembled parallelly same as case of Bagging but it differ in output prediction w.r.t case in Bagging.

Architecture of stacking:

Architecture is designed in such a way that it consists of two or more base/learner's models and a meta model that combines the predictions of the base models. Base model are called level 0 models and the meta model is level 1 model. This consist of original data, Primary level models, Primary level prediction, secondary level model and final prediction.



Original data: This data is divided into n -folds and is considered test/training data.

Base models: level-0 models that uses test/training data to provide compiled prediction.

Level-0 prediction: Each base model is triggered on same data and provides different predictions and called level-0 prediction.

Meta Model: Help best combine the predictions of base models and is called level-1 model.

Level-1 prediction: Meta model learn how to best combine predictions of base models and is trained on different predictions made by individual base models.

Example with calculation: [Ensemble Tech]

Consider below data:

Using Ada boosting.

Salary	Credit Sc.	Approval	Weight
$\leq 50k$	B	No	$1/7$
$\leq 50k$	G	Yes	$1/7$
$\leq 50k$	G	Yes	$1/7$
$> 50k$	B	No	$1/7$
$> 50k$	G	Yes	$1/7$
$> 50k$	N	Yes	$1/7$
$\leq 50k$	N	No	$1/7$

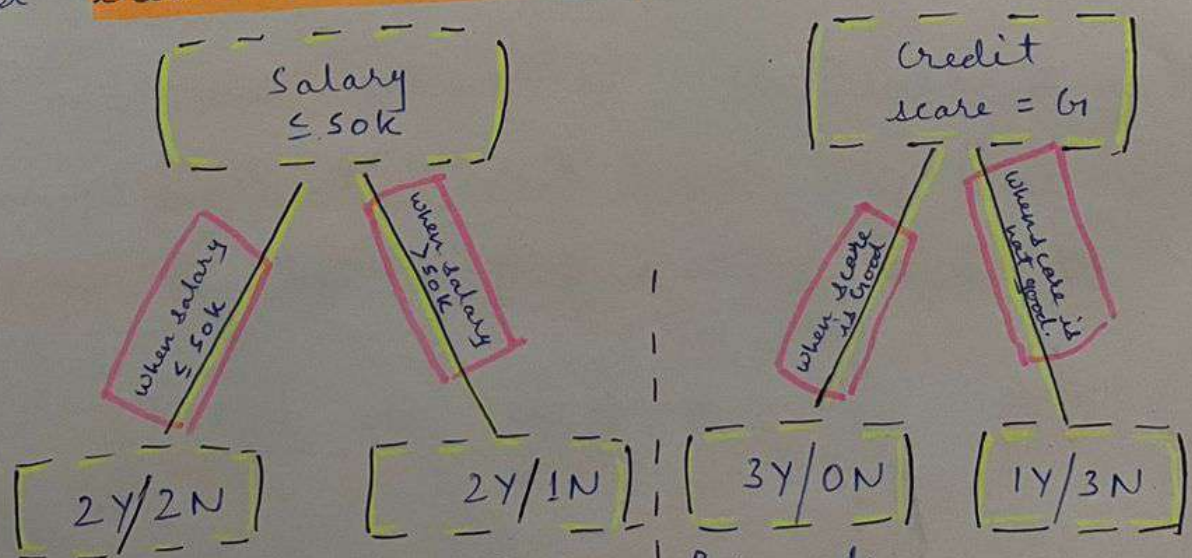
B : BAD

N : Normal

G : Good

As we have seven data points thus we have provided $1/7$ as initial weight.

Drawing decision Tree based on $\text{Salary} \leq 50k$ and $\text{credit score} = \text{Good}$.



we need to calculate Entropy or Gini-coef. for both the stumps and one having more. one we will go with it.

As the stump of credit score has a pure node so calculation is higher for it.

Thus, we will consider credit score for further calculation.

Salary	Credit Sc.	Approval	weight.
$\leq 50k$	B	No	$\frac{1}{7}$
$\leq 50k$	G	Yes	$\frac{1}{7}$
$\leq 50k$	G	Yes	$\frac{1}{7}$
$> 50k$	B	No	$\frac{1}{7}$
$> 50k$	G	Yes	$\frac{1}{7}$
$> 50k$	N	Yes	$\frac{1}{7}$
$\leq 50k$	N	No	$\frac{1}{7}$

For one row approval is given instead of having normal credit score. Thus that datapoint will be passed to further w.o.L

$$\text{Total error as of now} = \frac{1}{7} [\text{T.E}]$$

we will calculate further weight to update:

$$\text{Performance of stump} = \frac{1}{2} \ln \left[\frac{1 - T.E}{T.E} \right]$$

$$= \frac{1}{2} \ln(6) \approx 0.896$$

Now,

weight of first $w.L(\alpha_1) = 0.896$

Now,

weight of correct data points will be

updated one $= w_{\text{new}} = w_{\text{old}} \times e^{-\alpha_1}$

$$= \frac{1}{7} \times e^{-0.896} = 0.058$$

weight of wrong data points will be

$w_{\text{new}} = w_{\text{old}} \times e^{\alpha_1}$

$$= \frac{1}{7} \times e^{0.896} = 0.349$$

Updating New weights.

Salary	Credit sc.	Approval	w_{old}	w_{new}
$\leq 50k$	B	NO	$\frac{1}{7}$	0.058
$\leq 50k$	G	Yes	$\frac{1}{7}$	0.058
$\leq 50k$	G	Yes	$\frac{1}{7}$	0.058
$> 50k$	B	NO	$\frac{1}{7}$	0.058
$> 50k$	G	Yes	$\frac{1}{7}$	0.058
$\leq 50k$	N	No	$\frac{1}{7}$	0.058
$> 50k$	N	Yes	$\frac{1}{7}$	0.349
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As the sum of weight earlier was 1. So we need to standardize the updated weight as well.

Normalizing and assigning bins.

Salary	Credit Sc	Approval	weight	w_{new}	Normalized weight
$\leq 50k$	B	No	$\frac{1}{7}$.058	.08
$\leq 50k$	G	Yes	$\frac{1}{7}$.058	.08
$\leq 50k$	G	Yes	$\frac{1}{7}$.058	.08
$> 50k$	B	No	$\frac{1}{7}$.058	.08
$> 50k$	G	Yes	$\frac{1}{7}$.058	.08
$> 50k$	N	Yes	$\frac{1}{7}$.349	.5
$\leq 50k$	N	No	$\frac{1}{7}$.058	.08

Sum: .697

≈ 1

Now, dividing updated weight with it's total column sum to Normalize value b/w 0 - 1.

Normalized weight	Bin Assignment
.08	0 - .08
.08	.08 - .16
.08	.16 - .24
.08	.24 - .32
.08	.32 - .4
.5	.4 - .9
.08	.9 - 1

Thus, now we have the bin size k_{max} is of one having wrong data point.

Now, most of the weight data points will lie within that bin range [wrong one]

Then if predicted wrong data will further pass on to the further ML algo. Again if it continues wrong prediction we continue on increasing weight by using $[\text{weight}_{old} \times e^{\pm \alpha_i}]$ and decreasing for right one.

Lastly we will have weightage sum and we will take final output for yes/no accordingly whose weightage will be more.

In code we will do so by adjusting n -estimators to get best accuracy.

Even we can use combinations of base learners to have better accuracy in some cases. Ex - S.V.C, S.V.M.